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A machine learning method to predict printing time for the L-PBF process

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Abstract

The machine learning usage in the L-PBF process for metal powders helps to identify the optimal parameter combination. Machine learning can find non-linear correlations between the high number of variables of this production process. One of the obstacles to the widespread adoption of L-PBF in the industry, in addition to the high costs, is the long printing time required for a complex component. The possibility of an early evaluation of the 3D printing time could promote the overall diffusion of this production process in the industry. Correct time prediction can improve cost efficiency and production capacity, reducing energy consumption, environmental impacts, and lead time. This paper proposes a machine learning approach, such as Random Forest Regressor, to predict the printing time of a metal component starting from the STereo Lithography (.stl) CAD format for the L-PBF process. A case study is proposed to evaluate and demonstrate the approach, obtaining a high-level prediction accuracy.

Keywords: Printing Time; Machine Learning; L-PBF Process; Design for Additive Manufacturing.

1. Introduction

Additive Manufacturing (AM) is a set of production techniques characterized by being realized layer by layer. Standard ISO/ASTM 52900:2022 defines seven process categories: Binder Jetting, Direct Energy Deposition, Material Extrusion, Material Jetting, Powder Bed Fusion, Sheet Lamination, and Vat Photopolymerization [1]. AM enables the realization of complex and free-form geometries that are difficult or impossible to realize with traditional manufacturing techniques. Materials involved are polymers, ceramics, composites, pure metals, and alloys [2]. The high costs and long printing time, especially for the metal sector, are limiting the diffusion of AM in the industry. However, some factors are overturning this trend such as the high tooling costs related to subtracting manufacturing, the possibility of ongoing changes during the project phases, shorter time to market (agile reaction in all steps of the product life cycle), the design complexity allowed, the possibility of low/medium volumes production, the digital inventory, and the possible product customization.

Design for Additive Manufacturing (DfAM) is the discipline that studies tools and methods to overcome all technological constraints, related to materials and processes, and to optimize geometries [3].

AM is a digital process because it is based on the integration of digital tools, software, and workflows throughout the production cycle. Every phase of production can be related to a digital environment; the design phase uses CAD software to realize a 3D digital model that can be optimized using algorithms; the slicing phase and process planning such as the nesting phase, material deposition, layering, etc. are entirely digital and associated to the printer software, etc. [4].

The possibility of an early evaluation of the 3D printing time could promote the overall diffusion of this production process

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in the industry. Correct time prediction can improve cost efficiency and production capacity, reducing energy consumption, environmental impacts, and lead time.

The paper proposes a Machine Learning (ML) method based on Random Forest Regressor to evaluate the printing time in Laser-Powder Bed Fusion, considering STL files as input. The scope of the research is to support the technical and economic analysis of a component to be printed, reducing the lead time. The remainder of the paper is organized as follows. Section 2 shows a brief description of the state-of-the art. Section 3 presents the proposed approach to predict the 3D printing time of STL models. Section 4 reports the test case used to validate the proposed method. Section 5 reports the obtained results, and Section 6 ends with discussions and conclusions.

2. State-of-the-art

2.1. L-PBF process

In the Powder Bed Fusion category, for pure metals and metal alloys, the Laser-Powder Bed Fusion (L-PBF) process is strictly relevant, also called Selective Laser Meling. L-PBF guarantees good surface roughness and geometrical tolerance compared to other AM processes for metals. A high-energy laser, typically a fiber laser, is employed to melt the metal powder layers selectively. The laser scans the powder bed surface following the geometry of the part, obtained from a CAD model. Only the cross-section of the part is melted, and the metal particles fuse as they solidify. After one layer is solidified, the build platform lowers slightly, allowing a fresh layer of powder to be spread on top, and the laser once again melts the powder according to the part's design [5].

The main obstacles to the widespread use of this technique in production processes, in addition to industry reluctance to adopt new technology, are the relatively long printing time and the elevated costs related to materials and machines. Many strategies are being studied to overcome these problems. These include the use of more powerful lasers, which would imply higher energy consumption; the use of thicker layers, which would affect part finish and quality; the adoption of multiple lasers, which would increase the complexity and cost of machines; and the use of automation. However, the melting time of powders remains a technological constraint that cannot be overcome by the process [6].

Table 1. STL formats comparison.

Feature	ASCII STL	Binary STL
Human-readable	Yes	No
File size	Larger	Smaller
Editing	Can be edited in a text editor	Requires specialized software
Usage	Rarely used for large models	Preferred for 3D printing, CAM, etc.

A standard file format used in Computer-Aided Design (CAD) and 3D printing is a Stereolithography (STL) file. It represents three-dimensional models by dividing their surfaces into a series of triangle facets that together characterize the geometry and contour of the object. STL files can be stored in ASCII or binary forms; both represent the same 3D model but differ in how the data is stored and the file size [7]. Table 1 describes the main features and differences of the two formats. Since the STL format is the most used exchange format for CAD models, using the STL format as a starting file allows the model to interface with any software.

2.2. Machine Learning

Nowadays, ML is being adopted more and more in every sector of human life. Moreover, Industry 4.0 enables and promotes ML usage to accelerate, optimize, and control production processes [8]. ML is an artificial intelligence field that applies algorithms to identify links between data and information to solve problems that haven't been solved yet [9]. ML methods can be classified into Supervised Learning (SL), Unsupervised Learning (UL), and Reinforcement Learning (RL) methods. SL is one of the most significant and well-established categories of ML [10]. An input and output pair dataset is used to train SL algorithms. To create a prediction model, the SL algorithm examines this information to determine the relationships between independent characteristics and selected dependent variables. The model can predict unknown output values given a new input data set [11]. UL method can learn how to describe dataset input patterns using statistical approaches. Unlike SL methods, UL methods do not require explicit target outputs associated with each input [12]. Principal Component Analysis and K-Means Clustering are two examples of dimensionality reduction algorithms and clustering UL techniques. RL techniques are studied to address the problem of learning through interaction with the environment achieving a specific goal. RL approaches are mostly used in autonomous robots and control systems. The learner, called the agent, is the decision-maker. The environment is everything that constantly interacts with the agent. The Environment reacts to the activities chosen by the Agent by giving Rewards and introducing new scenarios to the Agent. The Reward values must be maximized by the Agent. Because the learning system's actions affect its subsequent inputs, the RL methodology is a closed-loop technique as outlined [13]. One of the most used and powerful SL methods are the Artificial Neural Networks (ANNs). ANNs are inspired by the way biological processes operate in the human brain. ANNs can process information in parallel and identify nonlinear relationships. The three main components of an ANN are node character, network topology, and learning rules. Node characteristics specify how the input is processed, such as the activation function, the number of inputs and outputs connected to a single node, and the weight assigned to each input and output. The arrangement and connections between nodes are mapped by network topology. The initialization and adjustment of the weights are determined by learning rules [14].

2.3. Machine Learning in AM and DfAM

ML methods, particularly the SL approaches, are widely used in the AM and DfAM sectors. These methods can be classified into four macro-levels such as the Geometrical

Design, the Process Configuration, the Costs Estimation, and the Process Monitoring (also called "in-situ" monitoring) [15].

At the Geometrical Design Level, ML methods are employed to support designers in the decision-making phases and where optimizations are necessary [16].

At the Process Configuration Level, the main activities are choosing the process parameters, characterizing the powder spreading, and optimizing process variables with the help of ML techniques. Some process parameters, such as laser power, layer thickness, powder size and distribution, scanning techniques, etc., are influenced and occasionally determined by the specific 3D printer and the chosen AM technique. These process variables significantly affect the component's mechanical characteristics, including density, fatigue strength, porosity, and surface roughness [17].

At the Cost Estimation Level, the analytical approach for calculating printing costs can be replaced with ML methods, capable of exploiting the similarities of the 3D geometry of parts and printing processes to identify relevant features [18].

The Process Monitoring Level, also named In Situ Monitoring, deals with using sensors to control and regulate the 3D printing process in real-time [19]. The time and cost of the printed parts can be greatly reduced to this level due to potential parameter adjustments. Among the processing-related faults that affect the metal AM process are cracks, delamination, distortion, rough surfaces, lack of fusion, porosity, foreign inclusions, and process instability (keyhole, balling) [20]. Sensors can identify potentially dangerous scenarios, and ML can avoid 3D printing errors. Other ML applications fall outside this classification. An example can be [21], a decision tree classifier (an SL method) was used to identify the printability of CAD models by analyzing some geometric parameters.

The next section shows and describes the proposed approach for 3D printing time prediction, starting from STL CAD files and using a Random Forest Regressor as ML model.

3. Proposed Method

Figure 1 shows the proposed approach that uses an ML method to estimate the 3D printing time of metal part to be realized with the L-PBF process. The method can be divided into different phases. The first phase concerns the realization of the dataset; the second phase regards the training and the tuning of the ML model, a random Forest Regressor; and the third phase uses the trained model to predict the 3D printing time of a part.

The dataset realization phase can be further divided into two other sub-phases. The first sub-phase concerns extracting features from the STL models using Python code and subsequently writing the extracted features on a spreadsheet. The second sub-phase concerns the estimation of the 3D printing time associated to a CAD model. This estimation can be achieved by virtual or physical 3d printing. Using virtual data to build the dataset reduces cost and training time. On the other hand, using real data is expensive but it provides more reliable results.

A Random Forest (RF) model is an ensemble learning method used primarily for classification and regression tasks. This ML method works by creating many decision trees during the training phase and combining their outputs to produce a more accurate and stable prediction [22]. These phases, called bootstrap and aggregation phases, are essential steps that work together to create a robust predictive model. During the bootstrap phase, multiple samples of the original dataset are randomly generated. Each tree is trained on a random subset of

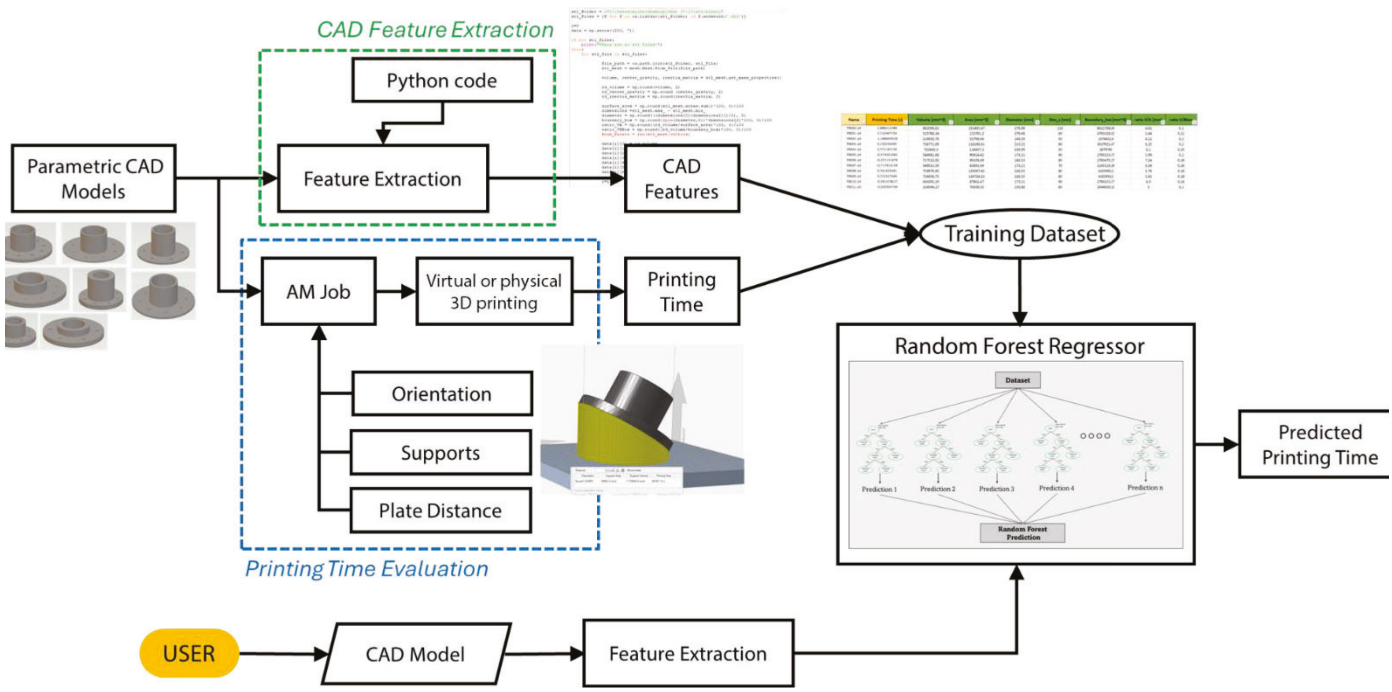

Fig. 1. Proposed Method for the printing time prediction.

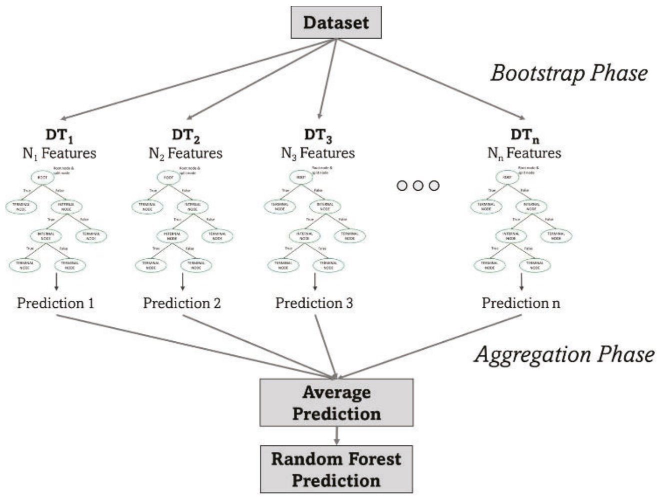

Fig. 2. Random Forest working scheme.

the data and sees only a fraction of the total information, introducing variety among the trees, making the forest more resilient to overfitting, as each tree offers a slightly different perspective on the data. In the aggregation phase, the predictions from each tree are combined to produce the final model output. For a classification task, aggregation involves using a majority voting system, where the predicted class is the one chosen by most trees. In regression, aggregation is realized by averaging the predictions from each tree, which results in a smoother, more accurate prediction [23].

Figure 2 shows the RF working scheme. Single trees in an RF are powerless learners, meaning each tree has limited predictive power. RF model is appreciated for its high performance, ease of use, and ability to handle large datasets and complex interactions among features. RF interpretability is also enhanced by feature importance scores, which indicate how much each feature contributes to predictions, making it a versatile choice for many practical applications.

Using the constructed dataset, the second phase trains and tunes the Random Forest Regressor. The selection of the right hyperparameters, and the choice of the features useful for training the model, can be a lengthy process. Three different metrics has been used to evaluate and compare training results such as the Mean Squared Error (MSE), the Mean Absolute Error (MAE), and the R^2 index, also known as coefficient of determination. Equation 1 describes the R^2 index.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y}_i)^2} \quad (1)$$

Where y_i represents the actual value of the target variable for the $i - th$ observation; $\hat{y}_i$ is the predicted value from the model; $\overline{y_i}$ is the mean of all actual values y_i in the dataset. $\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ is the Residual Sum of Squares, which measures the total squared prediction errors, $\sum_{i=1}^{n}(y_i - \overline{y_i})^2$is the Total Sum of Squares, which measures the total variance in the actual values. R^2 describes the proportion of variance in the actual data that is explained by the model. It is important to compare the variance in the prediction errors to the variance in data values. Concluding, R^2 provides a mathematical interpretation of how well a model captures the variance in the actual values.

The final phase involves using the trained model to evaluate the printing time of a CAD model that was not included in the training set. A Python script has been created to extract features from this STL file and utilize the ML model, achieving the desired goal.

4. Test Case

4.1. CAD models

To validate the proposed method, a set of two hundred parametric flange CAD models has been realized. Figure 3 shows some examples of these flanges. Each flange's geometrical parameter, such as the number and diameter of holes, the thickness of the plate and the axial extension, the length of the axial extension, and internal and external diameters, can vary in its specific range. For example, the external diameter can vary from 35 mm to 115 mm with steps of 5 mm. The total number of possible combinations is about two million. A DOE Latin Hypercube method was used to select the two hundred CAD models for training the RF. The CAD models have been automatically generated using a VB.net code previously developed [21].

The flange is not a useful component to study for metal AM, but its ease of parameterization allowed it to speed up the dataset creation times.

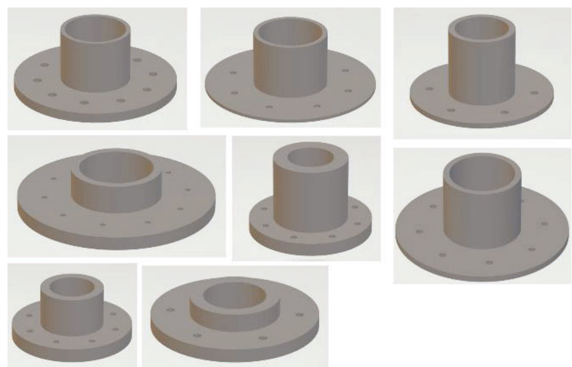

Fig. 3. Some examples of parametric flange models.

The parametric flanges' printing time was evaluated using the software Altair® Inspire™ 2024. The software uses the Inherent-Strain Simulation method [24] to simulate residual stresses and deformation during and after the printing process. Figure 4 shows an example of printing time evaluation with this software; this data has been used to complete the dataset. Table 2 reports the used setup for evaluating it. For each CAD model, the same printing set-up has been used.

Table 2. Software Setup to evaluate Printing time.

Parameter	Value
Build volume	300 mm x 300 mm x 250 mm
Orientation strategy	30° from building plate
Distance from plate	5 mm

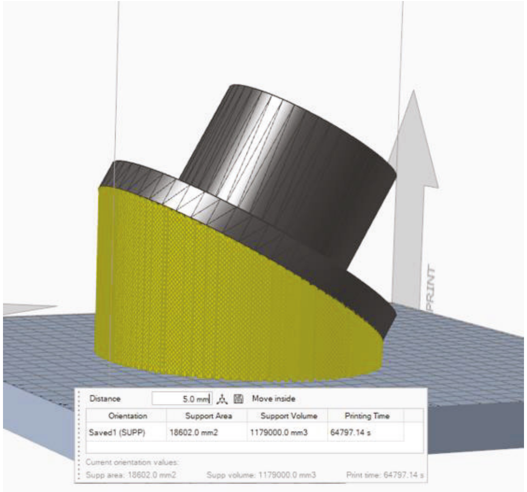

Fig. 4. 3D printing software Setup evaluated using the software Altair® Inspire™ 2024.

4.2. Data Preparation

The creation of the dataset involves three main steps: extracting data from STL CAD files, writing that data to a spreadsheet, and associating printing times with CAD models. The first two steps were accomplished using Python code, while the third step was completed manually.

Equation 2 shows the formula used to standardize each feature in the dataset. A standardized variable always has a mean of zero and a standard deviation of one. Standardization allows the comparison of variables that have means and standard deviations measured on different units of measurement and orders of magnitude.

$$z = \frac{x - \mu}{\sigma} \tag{2}$$

Where z is the new value of the variable, x is the starting value, μ is the mean of the feature, and σ is the standard deviation of the feature.

4.3. ML model

Hyperparameters play a crucial role in tuning the ML model's complexity, speed, and predictive accuracy. Table 3 shows the selected hyperparameters used to train the RF model in this study. The first one, the number of estimators (*n_estimators*), describes the number of parallel decision trees in the forest. A high value improves the model stability but increases the computation time. The second one (*max_depth*) characterizes the maximum depth of each tree. Deeper trees can capture more detail but pose the risk of overfitting. The third one (*min_samples_split*) shows the minimum number of samples required to split an internal node; with high values, the node needs more samples to split, leading to less model complexity and reduced overfitting. The fourth one (*min_samples_leaf*) describes the minimum number of samples necessary to be at a leaf node. The last one (*max_features*) considers the maximum number of features considered for splitting each node. This hyperparameter controls how many features each tree considers for splits, balancing diversity and accuracy in the ensemble.

Table 3. Hyperparameters for the trained Random Forest Regressor.

Hyperparameter	Value
n_estimators	200
max_depth	None
min_samples_split	5
min_samples_leaf	2
max_features	None

5. Results

Table 4 shows the obtained results, listing the three metrics used to evaluate the trained RF model, such as MSE, MAE, and R^2 . Each metric evaluates a specific aspect of the trained model. Low values of MSE indicate that the model's predictions are adjacent to the target values (0.0140 MSE was achieved; 0 is the perfect prediction). The values of MAE evaluate the average amplitude of errors without considering their positive or negative sign (0.0863 MAE was achieved; 0 is the perfect prediction). The R^2 score measures how the model's predictions match the data. R^2 values range from 0 to 1, the value 1 indicates perfect prediction and 0 indicates no explanatory power. In this case, the R^2 score suggests that 98.51% of the variance in the target variable is explained by the model. This high R^2 score confirms that the model fits the data very well.

Table 4. Evaluation metrics for the trained Random Forest Regressor.

Metrics	Value
Mean Squared Error (MSE)	0.0140
Mean Absolute Error (MAE)	0.0863
R^2 score Training	0.9911
R^2 score Test	0.9851

Figure 5 shows the comparison between the predicted printing time (red line) and test data (blue dots). Test data are fifteen percent of the dataset.

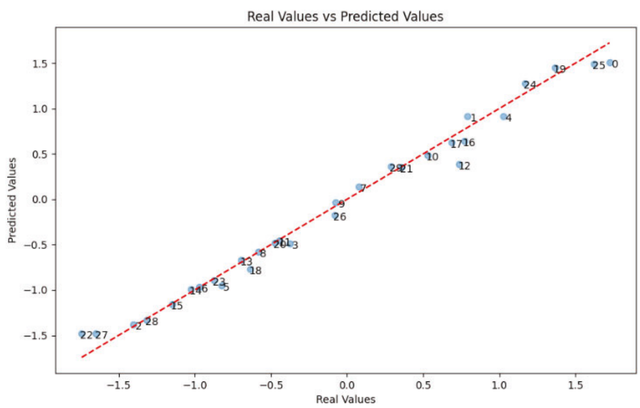

Fig. 5. Comparison between predicted values (red line) and real test values (blue dots).

Table 5 lists the obtained features relevance of the trained RF Regressor. Features relevance (or feature importance) represents how relevant each feature is in making predictions.

RF models provide feature importance scores by evaluating each feature's contribution across all the trees in the forest.

Table 5. Features relevance for the trained Random Forest Regressor.

Feature Relevance	Value
Volume	0.0022
Area	0.5619
Diameter	0.4236
Maximum Height	0.0008
Boundary Box	0.0091
ratio Volume/Area	0.0011
ratio Volume/Boundary Box	0.0013

6. Discussions and Conclusions

This work aims to provide designers with a method for the 3D printing time evaluation of metal parts, considering the L-PBF process. This paper proposes an ML method, based on a Random Forest Regression model, to predict printing time starting from STL files.

The ability to accurately predict printing times has the potential to enhance the efficiency and appeal of this production process. By optimizing the printing time estimation, manufacturers can improve cost efficiency by minimizing machine time and cost. A correct time estimation enhances better activities planning, improving the production capacity, and enabling a faster response to market demands.

The paper provides a research background on L-PBF process and STL CAD model files, on ML and Random Forest model, and on the actual usage of ML in AM and DfAM. The paper also validates the proposed approach using a case study, training a RF Regressor able to estimate the printing time of parametric STL CAD models. Even if only 200 cases were analyzed in the dataset, the test case shows good results in prediction achieving a 0.9851 R^2 score.

Currently, the proposed approach does not include the nesting technique, which involves filling the building chamber as much as possible to optimize time and costs. Future implementations will integrate this manufacturing technique, essential to become a real industry application. To further improve the method, geometries as varied as possible will be considered, as well as the influence of process parameters such as layer thickness, hatch spacing, plate distance, scan speed, orientation, etc.

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References

[1] Standard ISO/ASTM 52900:2022
[2] Bourell D, Kruth JP, Leu M, Levy G, Rosen D, Beese AM, Clare A. Materials for additive manufacturing. CIRP Annals, 66(2), 659–681; 2017.
[3] Trovato M, Cicconi P. Design tools for metal additive manufacturing: a critical and perspective overview. Procedia CIRP, 119, 1084–1090; 2023.
[4] Bonnard R, Hascoët JY, Mognol P, Zancul E, Alvares AJ. Hierarchical object-oriented model (HOOM) for additive manufacturing digital thread. Journal of Manufacturing Systems, 50, 36–52; 2019.
[5] Chowdhury S, Yadaiah N, Prakash C, Ramakrishna S, Dixit S, Gupta LR, Buddhi D. Laser powder bed fusion: a state-of-the-art review of the technology, materials, properties & defects, and numerical modelling. Journal of Materials Research and Technology, 20, 2109–2172; 2022.
[6] Wu T, Cheung EHM. Enhanced STL. The International Journal of Advanced Manufacturing Technology, 32(3–4), 422–422; 2006.
[7] Laleh M, Sadeghi E, Revilla RI, Chao Q, Haghdadi N, Hughes AE, Xu W, De Graeve I, Qian M, Gibson I, Tan MY. Heat treatment for metal additive manufacturing. Progress in Materials Science, 133, 101051; 2023.
[8] Rai R, Tiwari MK, Ivanov D, Dolgui A. Machine learning in manufacturing and industry 4.0 applications. International Journal of Production Research, 59(16), 4773-4778; 2021.
[9] Sarker IH. Machine Learning: Algorithms, Real-World Applications and Research Directions. SN Computer Science, 2(3); 2021.
[10] Cunningham P, Cord M, Delany SJ. Supervised Learning. Machine Learning Techniques for Multimedia, 21–49.
[11] Awad M, Khanna R. Machine Learning. Efficient Learning Machines, 1–18; 2015.
[12] Dayan P. Unsupervised Learning. The MIT Encyclopedia of the Cognitive Sciences. Wilson, RA Keil, F, editors.
[13] Sutton RS, Barto AG. Reinforcement learning: An introduction. London: MIT Press; 2018.
[14] Zou J, Han Y, So SS. Overview of Artificial Neural Networks. Artificial Neural Networks, 14–22; 2008.
[15] Trovato M, Belluomo L, Bici M, Campana F, Cicconi P. Machine Learning Trends in Design for Additive Manufacturing. Design Tools and Methods in Industrial Engineering III, 109–117; 2024.
[16] Babu, S. S., Mourad, A.-H. I., Harib, K. H., & Vijayavenkataraman, S. (2022). Recent developments in the application of machine-learning towards accelerated predictive multiscale design and additive manufacturing.
[17] Zhang M, Sun CN, Zhang X, Goh PC, Wei J, Hardacre D, Li H. High cycle fatigue life prediction of laser additive manufactured stainless steel: A machine learning approach. International Journal of Fatigue, 128, 105194; 2019.
[18] Chan SL, Lu Y, Wang Y. Data-driven cost estimation for additive manufacturing in cybermanufacturing. Journal of Manufacturing Systems, 46, 115–126; 2018.
[19] Jin Z, Zhang Z, Demir K, Gu GX. Machine Learning for Advanced Additive Manufacturing. Matter, 3(5), 1541–1556; 2020.
[20] Wang C, Tan XP, Tor SB, Lim CS. Machine learning in additive manufacturing: State-of-the-art and perspectives. Additive Manufacturing, 36, 101538; 2020.
[21] Trovato M, Cicconi P. A Decision Tree approach for an early evaluation of 3D models in Design for Additive Manufacturing. Procedia CIRP, 128, 96–101; 2024.
[22] Genuer R, Poggi JM, Tuleau-Malot C, Villa-Vialaneix N. Random Forests for Big Data. Big Data Research, 9, 28–46; 2017
[23] Mohammadtaheri H, Sedaghati R, Molavi-Zarandi M. Inherent strain approach to estimate residual stress and deformation in the laser powder bed fusion process for metal additive manufacturing—a state-of-the-art review. The International Journal of Advanced Manufacturing Technology, 122(5–6), 2187–2202; 2022.
[24] Fawagreh K, Gaber MM, Elyan E. Random forests: from early developments to recent advancements. Systems Science & Control Engineering, 2(1), 602–609; 2014.